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Clinical Analytics of Medical Data of Patients Using Natural Language Processing Approach

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Abstract: Clinical analytics is essential to the delivery of modern healthcare because it allows healthcare professionals to glean insightful information from massive patient data sets. Natural Language Processing (NLP) methods have become effective tools for healthcare textual data analysis in recent years. However, analysts' language evaluations are extremely individualized and vulnerable to the assessor's prejudices. Furthermore, language contains information that is typically hidden from observers. One potential approach to reducing the constraints of a person's evaluation of language is to supplement clinical evaluation with NLP. In this study, we investigate using NLP approaches to assess textual medical data and support evidence-based healthcare decision-making. There are various steps to the suggested strategy. First, the text is cleaned and standardized using the min-max normalization data preparation approach, which removes noise and extraneous information. Then, we aim to extract pertinent clinical data from various sources, including doctor notes, discharge summaries, and pathology reports, such as diagnoses, treatments, and patient outcomes. According to experimental findings, the proposed technology outperforms conventional techniques in clinical analytics of medical data with high accuracy, precision, recall, f1-score, the area under the curve (AUC), and lowest mean absolute percentage error (MAPE). Furthermore, NLP may be used to create predictive models that forecast patient outcomes or identify high-risk people for focused therapies. Significant implications for medical care and healthcare administration flow from the findings of this study.

Keywords*: Clinical analytics, medical data of patients, min-max normalization, natural language processing (NLP)*

1. Introduction

Clinical analytics is a discipline that uses data analysis to extract insightful knowledge from medical data, thereby enhancing patient care and healthcare decision-making. In the current digital era, enormous volumes of patient data are produced and kept electronically, providing previously unheard-of chances to extract useful information and support evidence-based treatments [1]. To get useful insights from patient-related data, clinical analytics of medical data use data analysis techniques. A vast amount of medical data is produced in the modern era of computerized healthcare, including Electronic Health Records (EHRs), data from medical imaging, test results, genetic information, and more. This vast amount of data is unlocked and transformed into knowledge using clinical analytics, which can be utilized to improve patient care, treatment outcomes, and medical decision-making. Medical professionals may use clinical analysis to extract significant patterns, trends, and correlations from patient data by utilizing advanced analytics approaches. Among the stages that make up this analytical approach are data gathering, integration, cleaning, preprocessing, and analysis. It involves employing analytical methods that are descriptive, predictive, and prescriptive to fully comprehend patient demographics, diseases, the efficacy of treatments, and resource allocation [3].

Patient medical information is stored in several systems in clinical and medical facilities. Additionally, details about medical devices such as sensors and computerized recorders are provided. Additional details might be kept in private data files, such as clinical database patient evaluation reports, household prescription records, and follow-up notes from primary care doctors. It is challenging for physicians to examine data and develop patient-related treatment recommendations due to the variety of data sources for patient information [4]. Clinical analysis refers to the data extraction process, the loading process, mining operations, visualization, and deduction processes carried out by clinicians in research and clinical institutions. The non-clinical patient data, such as economic, demographics, and behavioral facts, are evaluated further after the clinical analysis as a starting point. It is sometimes necessary to depict the analytical results to identify trends, potential treatment

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options, and other decision-support outcomes [5].

Given that medical data about patients is at the core of clinical analytics, practitioners and data scientists must adhere to regulations, and patient information must be deidentified to protect patient privacy and reduce the possibility that the patient might be individually recognized through direct or indirect inferences. To comply with privacy laws, methods including data disruption and masking data trajectory nodes might be utilized [6]. The examination of medical data and medical records has been transformed by the power of clinical analytics in NLP. A subfield of Artificial Intelligence (AI) known as NLP focuses on how computers and human language interact to analyze, interpret, and extract information from textual data. When used for clinical analytics, NLP brings important information concealed in unstructured medical data, including doctor's notes, laboratory states, and discharge summaries [7]. The study [8] clarified the use of personality identification tests in one's personal, academic, professional, or social life and offered potential techniques for carrying them out. Based on the person's sense of humor, one method for identifying personality research may be used. Studying a person's sense of humor has drawn psychologists' keen interest throughout the 20th century. There are several technologies for extracting radiomic characteristics, and the topic has received significant scientific impetus for standardization and validation. It is anticipated that the examination of molecular imaging by radiomics will offer a more thorough description of tissues than the parameters now in use. To optimize illness characterization and enhance clinical decision-making, the study [9] outlined the workflow of radiomics, the obstacles the field now confronts, and it is potential for inclusion in clinical decision-support systems. MRI has a great safety profile for patients, superb picture clarity, and is an excellent method for diagnosing brain tumors.

The evaluation of a brain MRI is crucial to patient treatment and decision-making. As a result, the study [10] suggested the Clinical Support System (CSS), which preprocesses the brain MRI image using a Genetic Optimized Median Filter before segmenting the brain tumor region using a Hierarchical Fuzzy Clustering Algorithm. Using the Gray-Level Co-Occurrence Matrix (GLCM) feature extraction approach, the characteristics of the tumor area are retrieved. Due to quick technical advancements and significantly lower costs, sequencing technology is increasingly being used in clinical laboratories rather than research [11]. Identifying the etiological agents for many diseases remains difficult, even though hundreds of microbes are known to infect people, as only a tiny number of pathogens are recognized by the existing diagnostic techniques. This caused the rise in popularity of metagenomic Next-Generation Sequencing (mNGS), a neutral, comprehensive method for the identification and taxonomy characterization of microorganisms.

To identify COVID-19 patients who are severely sick early and limit their mortality, the study [12] attempted to describe the clinical features of death cases with COVID-19. From the electronic medical records of 25 COVID-19-positive patients who passed away, the clinical data, laboratory results, and radiological evaluations, including chest X-ray or computed tomography, were retrieved. Primary hemostasis and thrombus development are greatly influenced by platelets. Following vascular damage, platelets cling to the wound site and quickly alter their structure, turning dormant platelets active. The origins, mechanism, diagnosis, and clinical ramifications of platelet activation were the main topics of the paper [13]. Platelets that have been activated group together and release physiologically active intermediates that, through autocrine and paracrine pathways, increase platelet activation.

Any area of life, including the medical industry, is quickly impacted by technological breakthroughs. The detection of diseases with the use of various AI technologies can be one of the solutions to regulate the current chaos. The research [14] used classical and ensemble machine-learning techniques to divide the textual clinical reports into four types. Techniques like Term Frequency/Inverse Document Frequency (TF/IDF), Bag of Words (BOW), and reporting duration were used to develop features. Due to a wide range of applications, including point-of-care monitoring of therapy and illness progression, discovering drugs, frequently employed food control, environmental monitoring, and biomedical research; biosensors are often used in biomedical diagnostic instruments. The paper [15] examined current developments in DNA base biosensors using various signal amplification techniques to identify pathogenic microbes, harmful metal ions, and cancer DNA and microRNA. In this paper, we demonstrate clinical analyses of patient medical data using the NLP methodology.

2. Methodology

In this section, we go through dataset collection, min-max normalization preprocessing, and NLP techniques for clinical analysis of patient medical data. The phases of the suggested technique are shown in Fig.1.

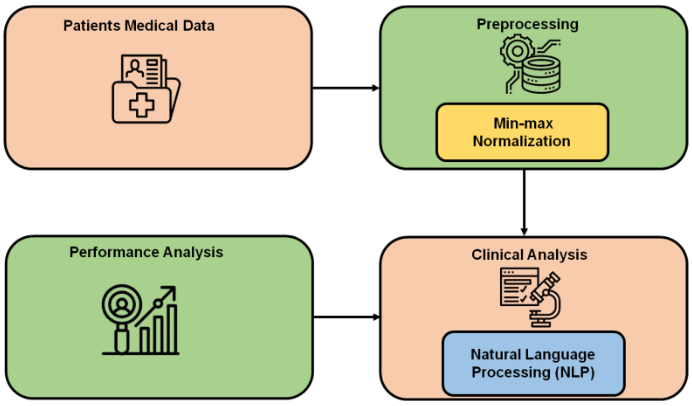

Fig.1. Stages of the proposed methodology

2.1. Dataset

This study uses HealthData.gov's original stroke dataset, also the standard data set utilized in a Kaggle contest. Details are presented in Table 1. The total number of 43400 collected examples, or approximately 1.17% of the dataset, contained 783 stroke patients, a typical class unbalanced type with 11 features. In addition, 325 elements from the dataset are missing, including 30% of the items related to smoking status and 3% of the variables related to body mass index (BMI). Different approaches will be used in the preprocessing to address this data-missing issue [16].

Table 1: Description of a dataset

Characteristics	Values
Gender	Male/Female
Patient ID	1-43400
Smoking status	Smoked/Formerly/Never
Work type	Private/Employed
Age	0.08-82
Residence type	Urban/Rural
Avg-glucose	55-291
BMI	10.1-97.6
Hypertension	Yes/No
Married	Yes/No
Heart disease	Yes/No

2.2. Preprocessing using min-max normalization

An important stage in data analysis and research in the healthcare industry is preprocessing patient medical data. Preprocessing procedures are crucial in maintaining the quality, consistency, and dependability of the data as EHRs and other medical databases become more widely accessible. Researchers and healthcare practitioners may enhance the precision and efficacy of future analysis by using various preprocessing techniques, which will result in better patient care, clinical decisions, and medical discoveries.

Medical data analysis is essential for evaluating patient health, spotting trends, and reaching well-informed judgments in healthcare. But numerical elements with various scales and ranges are frequently seen in medical data. When comparing or combining several variables for analysis, this difference may provide difficulties. To overcome this problem, the min-max normalizing method is frequently employed. Use the following steps to use min-max normalization to preprocess patient medical data:

- Identify the numerical variables that need to be normalized in the medical data. These characteristics may comprise physiological measures, laboratory findings, or other quantitative information.
- Find the minimum and maximum values in the dataset for each numerical attribute. The normalization procedure will make use of this range.
- Scale the values of each characteristic to a common

range (usually between 0 and 1) using the min-max normalization algorithm. The equation is as follows:

$$X_{new} = \frac{x=min}{max(x)-min(x)} \quad (1)$$

Where x represents the feature's initial value, min (x) represents its lowest value in the dataset, and max (x) represents its highest value.

- Apply the min-max normalization algorithm to each value of the numerical feature in the dataset, making sure to scale each data point independently.
- Replace the original values in the dataset with the matching normalized values once normalization has been completed for each data point and feature.
- Each feature utilized in the normalization procedure has to have its lowest and maximum values stored. If reversing the normalization is necessary for additional analysis or result interpretation, these parameters will be needed.

The numerical characteristics of the medical data will be converted into a common range using min-max normalization, making them acceptable for analysis and comparison. The relative correlations between various variables are preserved while the scale is normalized for subsequent processing or modeling.

2.3. Natural Language Processing (NLP)

AI has an area called NLP that focuses on how computers and human language interact. To allow computers to comprehend, interpret, and produce human language naturally and meaningfully, algorithms and models must be developed. The NLP mechanism is depicted in Fig.2.

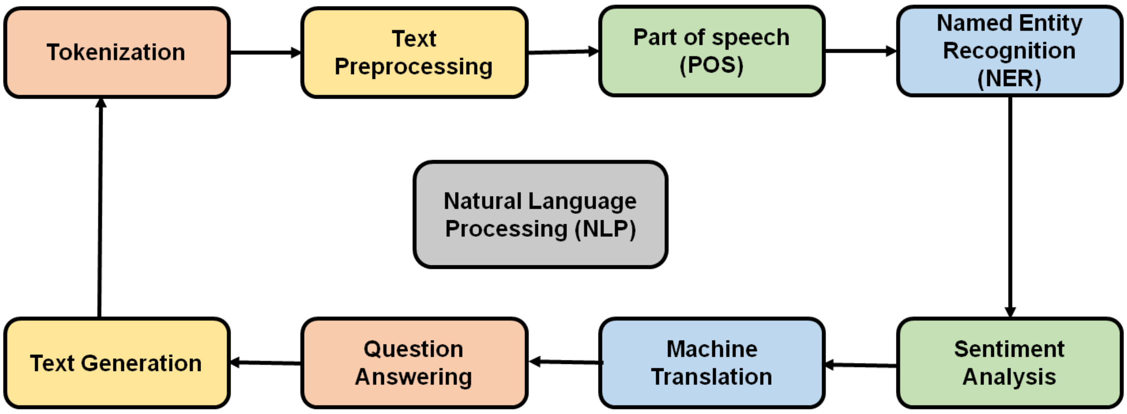

Fig.2. Natural Language Processing (NLP) Method

In NLP, a variety of strategies and methods are employed. NLP includes many different activities and uses, such as:

1. **Tokenization:** Tokenization is dividing a text into tokens, which are shorter units of text. These tokens might be single words or even more compact objects like letters or subwords. A crucial NLP process, tokenization facilitates the representation and analysis of text data.
2. **Text Preprocessing:** Text preprocessing entails converting unstructured, raw text data into a neater, more manageable format. This usually entails eliminating punctuation, changing the text's case to lowercase, eliminating stop words (commonly used words like "the" and "is"), in addition to addressing issues like stemming, which reduces words to their root form, or lemmatization, which transforms words into their base or vocabulary format.
3. **Part-of-Speech (POS) Tagging:** The act of tagging words in a phrase with grammatical categories (such as nouns, verbs, adjectives, etc.) is known as POS tagging. Information extraction, machine translation, and sentiment analysis all employ POS tagging to better comprehend the syntactic structure of a sentence.
4. **Named Entity Recognition (NER):** NER is locating and categorizing named entities (identified people, organizations, places, dates, and times, among others) in text into specified groups. Applications for NER include information extraction, question-and-answer systems, and many others.
5. **Sentiment Analysis:** Determine the sentiment or opinion expressed in a piece of writing by doing a sentiment analysis. Identifying if a text is favorable, negative, or neutral is involved. Monitoring social media, analyzing consumer reviews, and managing brand reputation all make extensive use of sentiment analysis.
6. **Machine Translation:** Automatically converting text between two languages is known as machine translation. Large volumes of bilingual text data are used by statistical and neural machine translation models to discover the patterns of language translation.
7. **Question Answering:** Systems that answer user

inquiries are designed to deliver accurate responses based on a context or knowledge base that has been provided. These systems often entail comprehending the query, finding pertinent data, and producing a brief response.

8. **Text Generation:** Based on a prompt or context, text creation includes producing cohesive and meaningful text. This might involve creating simple phrases and longer-form writing like articles or stories.

These are only a few illustrations of the techniques and jobs involved with NLP. With the help of deep learning models and extensive language pre-training, NLP techniques continue to progress quickly, providing increasingly complex language processing and generating capabilities.

2.4. NLP in Clinical Analytics

Clinical analysis of medical records can be used with NLP to gather insightful information and enhance clinical judgment. The application of NLP in this instance is summarized as follows:

- **Electronic Health Records (EHRs):** EHRs may contain unstructured clinical notes, discharge summaries, radiology reports, and other text data that may be analyzed using NLP techniques. Important data may be extracted using NLP, including patient demographics, medical problems, drugs, treatments, and test findings. By doing so, it is possible to create detailed patient profiles and help clinical decision support systems.
- **Clinical Classification and Coding:** Automating the labeling and classification of clinical data is possible with the help of NLP. This entails translating medical terminology into codes that are commonly used, such as ICD-10 (International Classification of Diseases) or SNOMED-CT (Systematized Nomenclature of Medicine - Clinical Terms). To increase the effectiveness and accuracy of coding activities, NLP models may be trained to detect pertinent medical ideas and give the proper codes.
- **Clinical Decision Support:** To assist healthcare practitioners in making decisions, NLP can help extract pertinent information from medical literature, clinical guidelines, and research publications. NLP systems can assist in clinical diagnosis, therapy suggestions, and warning physicians about potential medication interactions or adverse events by evaluating and summarizing the enormous volume of medical information.
- **Detecting adverse events and pharmacovigilance:** To monitor and categorize adverse medication responses or incidents, NLP may monitor and analyze textual data from various sources, including patient forums, social media, and electronic health records. NLP can aid in pharmacovigilance efforts and the early identification of possible safety problems by automatically collecting and evaluating patient-reported data.
- **Clinical Trial Analysis**: Clinical trial procedures, eligibility requirements, and research results may be used as structured data sources for NLP algorithms. NLP can help researchers and clinicians locate the right clinical trials for patients, identify appropriate cohorts, and synthesize the evidence for systematic reviews and meta-analyses by automatically collecting and evaluating pertinent data.
- **Phenotyping of patients and risk assessment:** Using NLP, it is possible to categorize patients based on shared clinical characteristics, identify patient phenotypes, and forecast illness risks or outcomes. To enhance personalized medicine and risk prediction models, NLP models may extract clinical traits, family histories, and lifestyle data from patient narratives and clinical notes.
- **NLP in Virtual Assistants:** Virtual assistants or chatbots for healthcare contexts can be created using NLP methods. These AI-driven systems can comprehend and interpret natural language inquiries from patients or healthcare professionals, deliver pertinent information, arrange appointments, respond to commonly asked questions, and make triage suggestions.

The use of NLP in clinical analytics necessitates strong data privacy and security measures to safeguard sensitive patient data, and it is crucial to mention this. To guarantee the moral and legal use of patient data, regulatory compliance with rules like Health Insurance Portability and Accountability Act (HIPAA) is crucial.

2.5. NLP as a clinical analysis interface

An intriguing endpoint for clinical analysis may be NLP. The general simplicity of getting the unprocessed data and the depth of the knowledge are advantages. Used for instance, a study participant may be requested to write down their response to a certain question at a predetermined time. Before using NLP for educational or professional medical study, certain challenges need to be addressed, in addition to the psychological tests that are discussed. The first step would be to demonstrate to a patient, a doctor, or a government agency that the data acquired is medically significant. Clinically outcomes that evaluate a person's sensations, functions, or survival are of interest to the Food and Drug Administration (FDA) in the United States. It should go without saying that NLP could not be used as a benchmark for any of the three factors. NLP and other biomarkers, however, can be regarded as substitute goals. Data demonstrating an association between an alteration in the substitute objective and an actual outcome, such as an operational measurement or a patient-reported result, is required to meet the criterion.

For a measure of NLP to be designated a surrogate measurement, FDA must demonstrate that it has a strong enough connection to direct measurement, but this is not immediately apparent to FDA. If NLP is intended to be the medical investigation's main objective, however, proving clinical significance is necessary. Additionally, officials would have to accept that an NLP assessed the elements it promised to evaluate. For example, if a treatment is being created for stroke victims displaying unfavorable symptoms, the objective would be to get permission for unfavorable emotions. It would be necessary to show that the NLP correctly identified undesirable symptoms at varying severity stages, a serious difficulty in various settings, including difficult cultural aspects. Additionally, the creation of medicines is almost often a worldwide project. Consequently, it would be necessary to analyze and validate the NLP measure in several languages.

3. Result and Discussion

In this section, we compare the performance of the suggested method to other well-established techniques, including Support Vector Machine (SVM) [17], Naive Bayes (NB) [18], and Random Forest (RF) [19] by computing accuracy, precision, recall, f1-score, AUC, and MAPE.

Accuracy is a metric used to evaluate the effectiveness and dependability of prediction models, diagnostic tests, and analytical algorithms in the clinical analysis of patients' medical data. It measures how effectively a model or test recognizes or anticipates the desired outcome. Predictive models and diagnostic procedures must be accurate for clinical analysis to be reliable, efficient, and usable in clinical settings.

$$Accuracy = \frac{(TP+TN)}{TP+TN+FP+FN} \quad (2)$$

Precision concerns the percentage of real positive outcomes among all the positive outcomes anticipated by a model or study. Precision is frequently used in clinical analysis to evaluate how well diagnostic tests, forecasting models, or algorithms detect positive instances within a particular population. A higher precision number denotes more accuracy and dependability in the study since it demonstrates a reduced percentage of false positives. The accuracy and precision comparison between the suggested technique and traditional methods is shown in Fig.3 and Table 2.

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

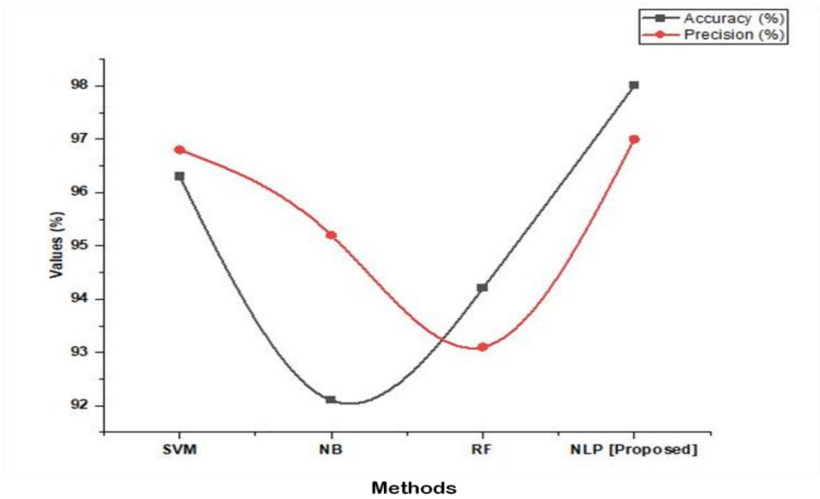

Fig.3. Accuracy and precision comparison of NLP with SVM, NB, and RF

Table 2: Comparison of accuracy and precision

	Values (%)	
Methods	**Accuracy (%)**	**Precision (%)**
SVM	96.3	96.8
NB	92.1	95.2
RF	94.2	93.1
NLP [Proposed]	98	97

Recall assesses a model's capacity to recognize or record all pertinent occurrences or events accurately. In clinical analysis, true positive is the proportion of real positive cases the model properly detected, and false negative denotes the proportion of real positive instances that were overlooked or ignored. A high recall shows that the model is capable of properly detecting and capturing positive cases.

$$Recall = \frac{TP}{TP+FN} \tag{4}$$

In clinical analysis, the **F1-score** is especially helpful when the dataset is unbalanced or when false positives and false negatives have varied outcomes. By reducing both types of mistakes, it offers a single metric that appropriately measures the model's total performance in correctly detecting positive situations. The recall and f1-score comparison between the suggested technique and traditional methods is shown in Fig.4 and Table 3.

$$F1 - score = \frac{2XPrecision\ X\ Recall}{Precision+Recall} \tag{5}$$

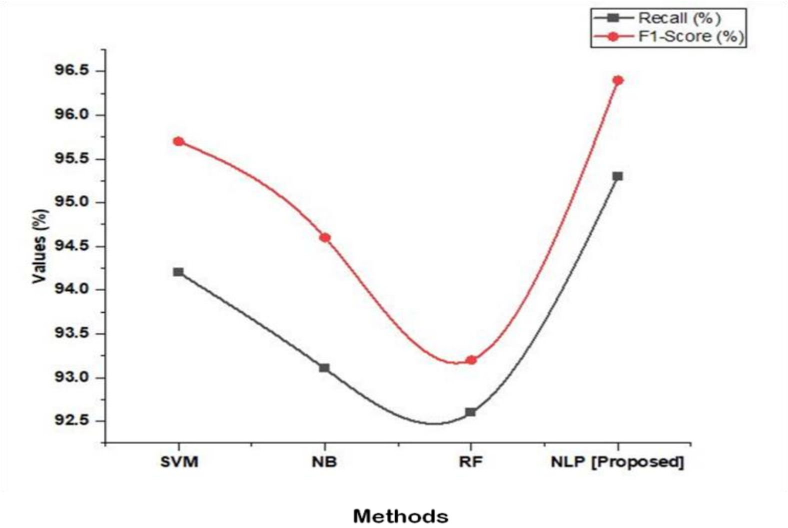

Fig.4. Recall and f1-score comparison of NLP with SVM, NB, and RF

Table 3: Comparison of recall and f1-score

	Values (%)	
Methods	**Recall (%)**	**F1-Score (%)**
SVM	94.2	95.7
NB	93.1	94.6
RF	92.6	93.2
NLP [Proposed]	95.3	96.4

The performance of a prediction model's receiver operating characteristic (ROC) curve is assessed using the **Area under the Curve (AUC)** statistic. The ROC curve shows the trade-off at different classification thresholds between the true positive rate (sensitivity) and the false positive rate (1-specificity). The probability that a randomly selected positive instance would be ranked higher than a randomly selected negative instance is shown by the AUC. It has a value between 0 and 1, with a greater value indicating better performance and discrimination. AUC of 0.5 denotes random performance, whereas 1 denotes a flawless model. Fig.5 shows the suggested method's AUC.

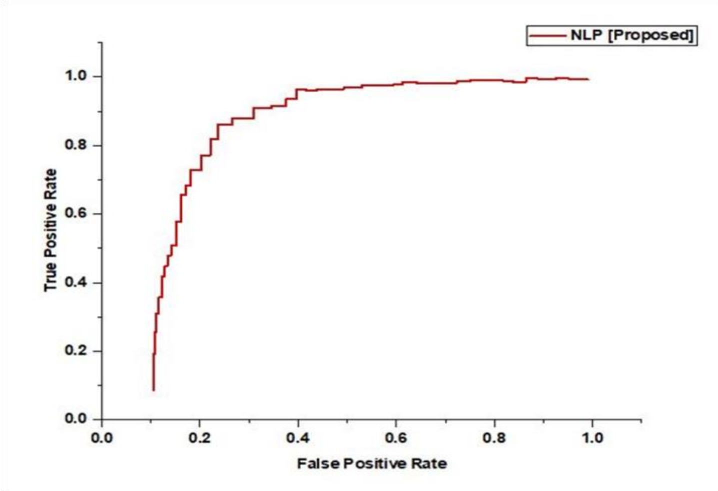

Fig.5. AUC of NLP approach

The average percentage difference between a dataset's projected values and actual values is what MAPE calculates in the context of clinical analysis. The relative difference between the expected and actual data is used to quantify the error's size. The prediction accuracy improves as MAPE decreases. The MAPE comparison between the suggested technique and traditional methods is shown in Fig.6 and Table 4.

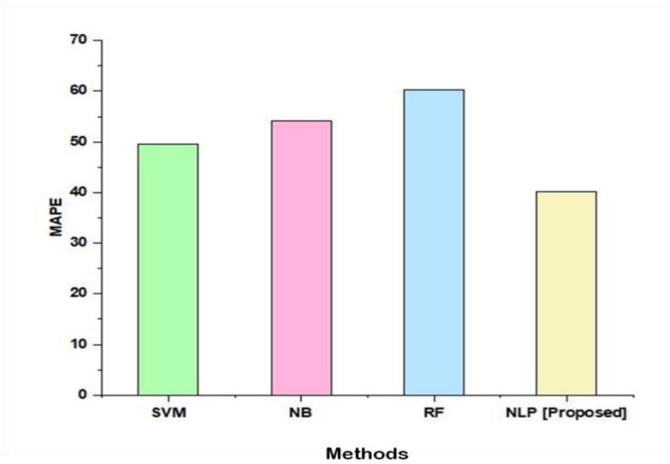

Fig.6. MAPE comparison of NLP with SVM, NB, and RF

Table 4: Comparison of MAPE

Methods	MAPE (%)
SVM	49.6
NB	54.2
RF	60.3
NLP [Proposed]	40.2

Based on the findings, NLP techniques have outperformed more conventional methods like SVM, NB, and RF regarding accuracy, precision, recall, F1-score, AUC, and MAPE. To extract valuable insights from textual data, NLP approaches use language processing and comprehension, which may be very useful in some fields and jobs. It's crucial to remember that the performance of various techniques might change based on the particular job, dataset, and implementation specifics. While classic machine learning methods like SVM, NB, and RF may still be useful in many situations, especially when working with structured data or when textual information is not the main emphasis, NLP has demonstrated encouraging outcomes in various applications.

4. Conclusion

According to this study, the use of NLP in the clinical analysis of patients' medical data has a great deal of promise to enhance healthcare results. Healthcare practitioners may improve knowledge discovery, tailored therapy, and decision-making by using NLP to extract insights from unstructured textual data. Using NLP approaches, it is possible to find patterns and signals in medical data that point to early illness indications or forecast outcomes. By delivering precise and pertinent information at the time of treatment, NLP-based clinical analysis promotes the use of evidence-based decision-making. It supports diagnosis, treatment planning, risk assessment, and monitoring, resulting in individualized medical strategies catered to the requirements of particular patients. It's crucial to remember that the selection of technique relies on the needs of the particular job, dataset, and challenge. SVM, NB, and RF have been utilized extensively and are still useful in many situations, especially when working with structured data or where interpretability is paramount. Ultimately, it is critical to evaluate and compare various approaches based on the specific context, dataset, and performance metrics to determine the most suitable approach for a given task in clinical analysis or any other domain, even though NLP has shown to be more effective in some applications.

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